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Introduction to the special issue on the Recognition of visible wavelength iris images captured at-a-distance and on-the-move

1. Overview

This special issue regards the recognition of degraded iris images acquired in visible wavelengths. During 2009 and 2010, the University of Beira Interior (Portugal) promoted two International evaluation initiatives about this subject, named Noisy Iris Challenge Evaluation (NICE) I and II. The first one focussed on the evaluation of iris segmentation strategies, considering that iris data acquired in visible wavelengths (VW) usually has much higher level of detail than traditionally used near infra-red data (NIR), but also has many more noise artifacts, including specular and diffuse reflections and shadows. Also, the spectral reflectance of the sclera is significantly higher in the VW than in the NIR and the spectral radiance of the iris with respect to the levels of its pigmentation varies much more significantly in the VW than in the NIR.

The NICE:II contest complemented its predecessor in terms of the traditional pattern recognition stages, evaluating different signature encoding and matching strategies. In order to guarantee that unbiased performance measures were obtained, all the participants used the exact same segmented data, which were automatically obtained according to the highest performing method in the NICE:I. Again, participation in NICE:II was free of charge and opened to all research and academic institutions. Sixty-seven participants from thirty countries registered in the contest [1] and received a training set composed of 1000 images and the corresponding binary iris segmentation masks.

The task assigned to participants is illustrated in Fig. 1: to construct a binary executable that receives (by command-line parameters) a pair of iris samples and their iris segmentation masks and outputs a text file containing a score that corresponds to the dissimilarity between the irises. This score d should be a metric, i.e., it should meet the following conditions: (1) $d(I,I) = 0$; (2) $d(I_1,I_2) = 0 \Rightarrow I_1 = I_2$ and (3) $d(I_1,I_2) + d(I_2,I_3) \geqslant d(I_1,I_3)$. In the evaluation, disjoint sets of 1000 unseen images and the corresponding segmentation masks were used to rank participants. Let $\mathbb{I} = \{I_1, \ldots, I_n\}$ be a set of iris images, $\mathbb{M} = \{M_1, \ldots, M_n\}$ their binary iris segmentation masks and $id(.)$ the identity function on an image. An *one-against-all* comparison scheme yields a set of *match* $\mathbb{D}^I = \left\{d_1^i, \ldots, d_m^i\right\}$ and of *non-match* $\mathbb{D}^E = \left\{d_1^e, \ldots, d_k^e\right\}$ dissimilarity scores, respectively, for the cases where $id(I_i) = id(I_j)$ and $id(I_i) \neq id(I_j)$. As suggested by Daugman, for two-choice decisions (e.g., *match/non-match*) the decidability index d' measures how well separated the two types of distributions are, and recognition errors correspond to their overlap area:

$$d' = \frac{|\mu_E - \mu_I|}{\sqrt{\frac{\sigma_I^2 + \sigma_E^2}{2}}}, \tag{1}$$

where $\mu_I = \frac{\sum_i d_i^I}{k}$ and $\mu_E = \frac{\sum_i d_i^E}{m}$ are the means of the two distributions and $\sigma_I = \frac{\sum_i (d_i^I - \mu_I)^2}{k-1}$ and $\sigma_E = \frac{\sum_i (d_i^E - \mu_E)^2}{m-1}$ their standard deviations. The participants were ranked according to their decidability scores, and the best eight were invited to publish their approaches in this special issue.

2. The special issue organization

Professor Kevin W. Bowyer was invited to publish a paper focused on the challenges of the recognition of iris images acquired in the VW and under less controlled acquisition protocols. The goal was to avoid the probable repetition of state-of-the-art sections in each participant's paper, given the focus of this special issue.

Papers appear in this special issue according to the classification of the NICE:II contest (Table 1). The best performing approach came from Tan et al. that performed biometric recognition according to both iris and periocular data. Global color-based features and local ordinal measures were used to extract discriminating data from the iris region, later fused to periocular data extracted from texton representations. Finally, fusion is performed by the sum rule using the normalized scores generated for the different types of features. Wang et al. used an adaptive boosting algorithm to build a strong iris classifier learned from a set of bi-dimensional Gabor-based set of features, each corresponding to a specific orientation and scale and operating locally. Later, given the fact that the pupillary boundary is especially difficult to segment in VW data, the authors trained two distinct classifiers: one for irises deemed to be accurately segmented and another for cases in which the pupillary boundary was not accurately segmented. Santos and Hoyle fused a set of recognition techniques that can be

[1] http://nice2.di.ubi.pt/registered.htm.

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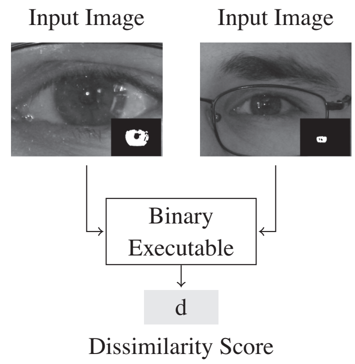

Fig. 1. Fundamental task of the NICE:II iris recognition contest. Participants had to produce a binary executable that receives a pair of VW iris images and their segmentation masks and outputs a numerical value that gives the dissimilarity between the irises.

Table 1
NICE:II classification.

Rank	Authors	Affiliation	Decid. (d')
1	Tan et al.	Chinese Academy of Sciences	2,5748
2	Wang et al.	Techshino Biometrics Research Center, Northeastern University	1,8213
3	Santos and Hoyle	University of Beira Interior and Universidade Federal do Rio de Janeiro	1,7786
4	Shin et al.	Biometrics Engineering Research Center, Dongguk University	1,6398
5	Li et al.	Heilongjiang University	1,4758
6	Marsico et al.	University of Salerno	1,2565
7	Li and Ma	Heilongjiang University	1,1892
8	Szewczyk et al.	Technical University of Lodz	1,0931

divided in two main categories: wavelet-based textural analysis methods applied to the iris region, complemented by distribution-based (histogram of oriented gradients and local binary patterns) and scale invariant feature transforms that analyze the periocular region, which was recently suggested as an important addition for handling degraded samples, essentially because it is less vulnerable to problems resulting from deficient illumination or low-resolution acquisition. Shin et al. started by classifying the left and right eyes by their eyelash distributions, which they used to reduce the search space. Further, they coupled two encoding and matching strategies based in color and textural analysis to obtain multiple distance scores fused by means of a weighted sum rule, which is claimed to improve the separation between *match* and *non-match* distributions. Li et al. used a novel weighted co-occurrence phase histogram to represent local textural features. This method is claimed to model the distribution of both the phase angle of the image gradient and the spatial layout, which overcomes the major weakness of the traditional histogram. A matching strategy based on the Bhattacharyya distance measures the goodness of match between irises. Finally, the authors concluded that the performance is improved when a simple image registration scheme accounts for the image deformation. Marsico et al. proposed the use of implicit equations to approximate both the pupillary and limbic iris boundaries and perform image normalization. Next, they exploited local feature extraction techniques such as linear binary patterns and discriminable textons to extract information from vertical and horizontal bands of the normalized image. Li and Ma introduced an image registration method based on the Lucas–Kanade algorithm to account for iris pattern deformation. Operating on the filtered iris images, this method divides the images into small sub-images and solves the registration problem for each small sub-image. Later, a sequential forward selection method searches for the most distinctive filters from a family of Gabor filters, concluding that a very small number of selected features are able to obtain satisfactory performance. Finally, Szewczyk et al. presented a semi-empirical approach based on a reverse bi-orthogonal dyadic wavelet transform, empirically selecting a compactly supported bi-orthogonal spline wavelet for which symmetry is possible with FIR filters and three vanishing moments. The authors concluded that such a method produces a short biometric signature (324 bits) that can be successfully used for recognition under such challenging conditions, improving its reliability.

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